Robots and Protest: Does Increased Protest Among Chinese Workers Result in More Automation?

Abstract

The rising level of automation has increasingly attracted scholar's attention. On the other hand, there are many studies of the consequences of social movements, but relatively fewer studies focus on their economic consequences, and even fewer studies have examined their consequences on automation. This article bridges the gap between the two literatures by hypothesizing that a rising number of labor protests will lead to a higher level of automation. We argue that political economy factors influence the adoption of more automation. Protests anticipate higher wages and labor costs; contest for social power with employers and the state, and, in extreme cases, pose a public relations challenge to employers, which will likely push employers to replace human workers with robots. We empirically test the relationship by using two protest event datasets in China, the China Labour Bulletin (CLB) and Collective Action from Social Media (CASM), and robot data from the International Federation of Robotics (IFR). Statistical analysis shows that provinces and industries that have more protests also tend to concentrate more robots, and the results are robust to most specifications and placebo tests. The findings have implications for both understanding the mechanism explaining rising automation and the consequences of social protests.

Keywords: Automation, Protest, Strike, Social Movements, China

JEL Classification: O33, J50

Introduction

There have been increasing concerns about automation in the recent past, which involves the systematic replacement of human labor by technology (Collins 2013; Brynjolfsson and McAfee 2014; Ford 2015; Borjas and Freeman 2019; Acemoglu and Restrepo 2020; Parolin 2021). Classical sociology has identified technology as the primary engine of capitalism and the rational economic order (Marx 1867; Weber 1961; also see Collins 1980). Previous empirical studies have examined the social consequences of automation on various communities. Automation is one of the underlying drivers of deindustrialization in US mid-western industrial cities that became pockets of deprivation (Wilson 1987) and deteriorating health indicators (Case and Deaton 2015).[1] At a macro-social level, increasing technological investments have been associated with growing managerial power (Goldstein 2012); rising inequality (Kristal 2013; Autor and Salomons 2018), declining union power (Kristal 2019) and the rise of right-wing nationalism (Anelli et al. 2021). Other studies have treated automation as a phenomenon to be explained. Rapidly aging societies and low-immigrant community regions are faster to automate (Acemoglu and Restrepo 2018; Liu and Portes 2020).

On the other hand, the study of causes of protests and social movements have a long and mature history, but empirical studies on their consequences are relatively new. Existing studies have examined individual, cultural, as well as political consequences of protests (McAdam 1989; Giugni 2008; Amenta et al. 2010; Vestergren et al. 2017). But not much has been known about economic consequences of contentious politics. Some studies have been focused on how

[1] There is a debate about whether automation or outsourcing primarily accounts for a loss in US manufacturing jobs. Both accounts are plausible by the economic evidence.

contentious politics has brought institutional change and innovation to markets (King and Pearce 2010; Vasi and King 2012).

This article contributes to the literature of contentious politics as well as social studies of contributing factors to automation by creating a direct link between these two phenomena. It argues that increase in labor protests will lead to a higher level of automation. It is because labor protests would likely result in higher wage costs, cause instability and troubles for employers, and hurt employers' bargaining power while giving labor protesters more bargaining power. Replacing workers with robots would not only reduce the operational cost for employers in the long run, restore managerial control for remaining workers and reduce employers' risk of being targets of protesters. Therefore, when labor protests that advocate for economic rights or higher wages are increasing in a region or industry, we expect that employers in that region/ industry would have a higher incentive to replace human workers with robots, thus increasing the level of automation. However, an alternative argument is also plausible: an increase in labor protest will lead to less automation. This is because strikes add pressure to companies and force them to make concessions to protesters to keep them, instead of replacing humans with machines. This counterargument is plausible at least in the short term (Card and Olson 1995).

We choose China as our empirical case. We argue that in China, labor protest led to higher, instead of lower level of automation. Chinese economic reform since 1978 have induced many rural migrant laborers to move to the coastal cities for factory work (Gallagher 2014; Naughton 2007: 129-31) and this development has led to thousands of labor protests each year, and the number may still be rising. In particular, 80% of strikes and labor protest are linked to wage arrears (CLB 2019). Chinese labor contention can partly be explained by China's position as factory of the world unlike western industrial countries where industrial plant investments have been declining and unions are fighting rearguard battles (Estlund 2017). In China, increased labor contention may have contributed to more bargaining leverage for workers (Butollo and Brink 2012). Manufacturing wages have tripled from 24,000 RMB in 2008 to 64,000 RMB in 2017.[2] The increasing old-age dependency ratio and aging society are furthering labor-shortage induced wage rises. Between 2015 to 2050, the working-age population is expected to decline from 1 billion to 800 million (Lin 2015: 78; Citigroup 2016). With rising wages and labor shortages, Chinese manufacturing companies are increasingly less competitive and have been advocating for factory relocations to other interior provinces (Fan 2018), abroad (Thomson Reuters 2016), or to automate production altogether (Bateman 2018; Rozelle and Hell 2020).

Simultaneously, the Chinese government has been supporting the drive toward automation, announcing to increase industrial automation by tenfold and hike manufacturing value added from 2015 to 2025 (State Council 2015; He and Leng 2019). The desire to automate and develop modern technology is a highly ideologically motivated decision (Coplin 2019; Greenhalgh and Zhang 2020). The 2017 government directive titled "New Generation Artificial Intelligence Development Plan" (*xin yidai rengong zhineng fazhan guihua*) laid out the strategic significance of China being on the cutting edge of developing artificial intelligence (AI) and robotics. For the Chinese government, the development of AI is part of the 200-year struggle of the Chinese nation to "rejuvenate the Chinese dream" (State Council 2017). In a speech to the Chinese Academy of Sciences, President Xi Jinping (2014) cited a report on the "robot revolution" and argued that China had to be at the forefront of it. Furthermore, the policy directive claims that expected replacement of work can be managed by lifelong learning.

[2] Trading Economics ("China Average Yearly Wages in Manufacturing") https://tradingeconomics.com/china/wages-in-manufacturing

Given the high level of labor contention and its pressure on employers, as well as the development of AI that provided employers with cheaper robots as well as policy support, we argue that the hypothesized positive relationship between labor protests and robots holds in China. Some famous cases support our argument. When the workers at the Apple supplier Foxconn jumped from a building to commit suicide citing high stress and low pay (Chan et al. 2013; Pun 2016: ch. 6), the resulting public relations disaster induced Foxconn to announce mass automation. Of the 1 million promised robots only 50,000 had been installed as of 2015, which suggests that automation is not a straightforward transition process (CLB 2019). On the other hand, Foxconn has already replaced 400,000 jobs between 2012 and 2016 (ChinaPower 2018). Moreover, simple descriptive plots suggests that the number of protests and robots are both increasing (Figure 1).

INSERT FIGURE 1 HERE

The Foxconn case as well as the trend plots all provide intuitive support for our argument. Will the relationship hold under empirical scrutiny when other confounders are controlled for? Drawing from two Chinese protest event datasets that measures labor strike activity including China Labour Bulletin (CLB) and Collective Action from Social Media (CASM), and the International Federation of Robotics that measures robot exposure, we find that industries and provinces with a higher strike activity experience more robotization from 2011 to 2015. In addition to demographic factors, international competition for cost-competitive production, and the state of technological innovation, we argue that there is a political economy logic for automation, whereby the presence of labor strike activities can predict an accelerated drive toward automation. In other words, labor-displacing automation is a firm-level response to labor protests.

Although this study focuses on China, we also do not see China as a special case. Rather, we see China as exemplary case that could be indicative of the future of labor protests and automation elsewhere. In particular, China's Belt-Road initiative, which involves the shifting of production capital from China to less developed low-wage labor countries, augurs the potential export of China's labor conflict and automation model beyond its boundaries. That is, the mechanism we proposed and empirically identified in China could travel elsewhere, especially other low-wage labor countries, such as Vietnam. In the countries where manufacturing jobs are moving to, a similar process may occur if workers there also experienced wage arrears and labor protests, which may drive governments to follow similar procedures as China did, especially when the Chinese government is also actively engaged in exporting technologies overseas. In this regard, our article has potential implications from a general comparative political economy perspective.[3]

Consequences of labor protests on firms

Labor protests can have negative reputational effects on firms. Poor environmental and labor standards heighten the demand for corporate social responsibility or risk public and consumer mistrust (Schnietz and Epstein 2005). Strike activity is associated with stock price declines (Dinardo and Hallock 2002). Protests also challenge firms' ability to set pay and working

[3] On the other hand, western countries at a later stage of industrial development are less suitable for linking protests with automation, although the link still exists in workplace case studies, e.g., US longshoremen protests amid automation.

conditions. Labor protests can induce companies to offer more benefits and welfare measures to provide more industrial stability (Rajala 1989). Another possibility is that firms react to protest activity with repression, i.e. closing and moving plants (Kirkham et al. 1999; Fan 2018), hiring replacement workers (Krueger and Mas 2004) or layoffs (Uchitelle 2007). An underexplored link is whether labor protests are related to automation.

Labor control and displacement via technologies

A possible firm response to labor unrest is resorting to technology. Technology produces two possible outcomes: firstly, it standardizes the workflow and increases managerial control by deskilling labor tasks (Braverman 1974; Noble 1984). Deskilled workers are more easily replaced by new workers, who do not need extensive training, which, in turn, makes union or strike activity more complex (Braverman 1974). Technology also strengthens labor surveillance (Reich and Bearman 2018; Griesbach et al. 2019; Lei 2021). Secondly, automation in the industrial sector shrinks the unionized workforce (Handel 2015) and obviates the future possibility of strikes (Cokelaere 2020). In either case, firms can use technology to contest for social power with workers and have a vested interest in using more of it.

To build an intuition for this relationship, one may consider the key finding of the China Employer-Employee Survey: managers report high labor costs as the most common concern to firm survival and well-being (Wuhan University 2017). 60% of managers report high labor costs as the biggest barrier to firm development, which is higher than other perceived barriers (i.e. market demand, technical skills of workers, tax or financial access). The same survey reports that 8% of the firms have robots, which is higher in Guangdong (10%) than in Hubei (6%) with the machine, electronics and metal industries concentrating most robots (Wuhan University 2017). These wage concerns are driven by the fact that workers have been increasingly scarce, but also that via protests these workers are able to force employers into granting these higher wages (Butollo and Brink 2012), which make automation a more attractive option.

Finally, labor protests that garner much public attention, such as the string of worker suicides among Foxconn workers in 2010, are a public relations disaster for companies, who, as in the case of Foxconn, may be motivated to seek innovation and technology to replace workers and reduce the demand for labor in the future. Therefore, both technology-driven labor control strategies as well as public relations logic predicts that companies will have a strong incentive to replace humans with robots in the presence of labor protests.

On the flipside, it is conceivable, at least over the short term, that labor unrest diminishes automation. First, in response to unrest firms have to spend more funds on company benefits (Rajala 1989) which creates obstacles for costly technological investments. While such a financial obstacle does not apply to the biggest firms who have substantial financial cushion and can raise more on the stock market, it could deter other small to mid-size firms. Second, some labor protests may explicitly be about opposing the attempts to replace humans by machines, such as taxi drivers protesting against self-driving cars (Kaminska 2019). If the government steps in and decides to protect workers' rights and help them collectively bargain with the company to boost employment or to obtain voting support from labor unions, labor protests against automation could lead to less automation. While this type of protest may not constitute most labor protests, it is worth mentioning this possibility.

We next discuss the labor and automation context in China, in which the government does **not** help protesters in attaining collective bargaining with private companies, but rather plays a proactive role in fostering automation.

The Chinese State Influencing Automation

The effort to automate has been the official government policy in China (Citigroup 2016). The push for automation is partly driven by the concern of the shrinking labor force in the very near future. Moreover, the government believes that by investing in automation technologies and related artificial intelligence, they can catch up with the US in science and technology development and replace the old labor-intensive manufacturing industries with human-capital intensive new manufacturing (Au 2020). The Chinese private sector---especially the technology giants Baidu, Alibaba, and Tencent---, universities, and government have developed three major AI research hubs in Beijing (242 AI companies in 2016), Shanghai (112) and Shenzhen (93) (He 2017). Tsinghua University published a report describing the research advances in AI. Chinese scientists are producing more papers and patents on AI (37,000 papers in 2017) than their US counterparts (25,000). On the other hand, the US has an advantage in AI talent compared to China (28,000 vs 18,000) (CISTP 2018). With respect to industrial robotics, China's robot density in 2016 was slightly below the world average, but it grew substantially in the recent past. The government target is to raise robot density to 150 units per 10,000 workers (IFR 2018). The Chinese cost advantage can be maintained if it invests more heavily in automation (Citigroup 2016).

In 2017, Guangdong province, which contains the country's major manufacturing base, pledged to invest 943 billion yuan by 2020 in automating production (Economist 2017), although Sharif and Huang (2019) argue that official government policies play a limited role, while the competitive market environment is very influential in driving automation. The consulting firm PwC (n.d.) predicted that in the 2017-37 period, automation will only result in substantial job losses in the agriculture sector (-10%), while manufacturing marginally changes (+3%), and substantial gains are found in the service (+29%) and construction (+23%) sectors. Automation in Guangdong's garment industry has resulted in rising productivity, but also speed-up and deskilling (Butollo 2015: 93). Very importantly, for the purposes of our study, given that the state aggressively pushes automation the variation in automation outcomes is, in part, explainable by other factors including labor protests.

How the Chinese government deals with Labor Protests

The "vigor of Chinese workers' activism stands in sharp contrast to the state of labor movements in other transitional and developing countries" (Gallagher 2014: 82). In China, the number of protests has been increasing since the 1990s (Lee and Zhang 2013). The Chinese state fears the formation of an independent trade union movement that threatens the power of the state (Estlund 2017) and centralized the power of collective bargaining to the All-China Federation of Trade Unions, an arm of the Communist Party, whose officials are accountable to the party hierarchy rather than the workers and thus rarely solve workers' grievances (Friedman 2014). The state will suppress others from forming their own labor unions and organize collective action, forcing workers to protest alone instead of organizing collectively, e.g. via wildcat strikes. Alternatively, Lee and Zhang (2013) argue that the state uses "bargained authoritarianism" in the form of cash payoff, threat of force, mediation, litigation and petitions to channel workers into compliance rather than mobilization. The suppression and co-optation from the state forces the protests to be localized and restricted to narrow economic issues within a single factory, which Lee (2007) coined "cellular activism" (also cf. Friedman 2014; Friedman and Kuruvilla 2015; Kuruvilla and Zhang 2016). Given the repressive state apparatus, labor NGOs often avoid building formal workplace organizations and encourage workers to use individualized and informal means such as negotiating directly with officials for concessions and in some cases even threaten suicide (Fu 2017). In sum, the state is critically concerned about the threat of labor organizations and does not support workers to organize collectively to bargain with private companies. As noted earlier, the state is also treating automation as a top policy priority. These two factors, taken together, favor the explanation that rising labor protests increase automation, not decrease it. Next, we discuss our data and empirical strategies that test the association between robot density and labor protests.

Data

The explanatory variable is the number of protests in a year, industry and province. Protest data comes from two sources, the China Labour Bulletin (CLB) and Collective Action from Social Media (CASM) (Zhang and Pan 2019). China Labor Bulletin is a Hong Kong-based NGO that aims to help workers bargain with employers and advocate for their rights. Since 2011, CLB has been gathering and publishing labor-related protest cases in China on their website and has built an interactive map (CLB Strike Map) for the protest cases they collected. The limitations are twofold. CLB's website recognizes that it may significantly understate the true extent of strikes.[4] Second, CLB is not explicit about how they collected the data (e.g., the data sources, sampling criteria, and search keyword used), such that we could not know if there is any systematic bias in the distributions of protests.

CASM is data collected by Zhang and Pan (2019), who developed a two-step deep learning algorithm based on text and image data to identify offline collective action events from 9.5 million Weibo (a Twitter analog in China) posts that contained at least one of 50 general protest-related words. CASM contains more than 136,330 offline protest events in China from 2010 to the middle of 2017. Each protest is located at the county level. The dataset and replication materials are publicly available.[5] CASM differs from CLB in three important ways. First, CASM aims to collect protests of any kind, including but not restricted to labor protests. In fact, the majority of protests (76%) in CASM is non-labor related, which serve as a placebo test: an increasing number of non-labor protests should *not* be associated with higher level of automation, which we will verify in presenting results. Second, even restricting to labor protests, CASM still has more protests than CLB. Third, CASM is transparent about the data sampling and construction process. The drawback of CASM is that each protest is identified by machine learning, albeit with high accuracy, whereas each protest in CLB is verified by humans in CLB. The two datasets have some overlap. Zhang and Pan (2019) show that 75% of protests in CLB in the first half of 2016 are also in CASM.[6]

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[4] https://clb.org.hk/content/introduction-china-labour-bulletin's-strike-map. The website is explicit about variables associated with each protest, such as how they coded action types, response to protests, etc. But they do not specify how the protest events are collected in the first place.

[5] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SS4LNN

[6] The reverse number is unknown, partly because CLB contains only labor-related protests but CASM contains protests with different issues so it is not meaningful to calculate what proportion of protests in CASM is also in CLB. Zhang and Pan (2019) also did not calculate such proportion.

Both datasets may underestimate the true number of protests on the ground. Their data collection may be further complicated with the government's increasing censorship of social media (Roberts 2018; Hernandez 2019), although Zhang and Pan (2019) have shown that censorship does not lead to major undercoverage of protests on social media.[7] In the absence of official government statistics on employment-related strikes (Friedman and Kuruvilla 2015; Kuruvilla and Zhang 2016), which will also unlikely be available in the foreseeable future, the two datasets provide the best data source at this moment. We restrict both datasets to be within 2011 and 2015, during which we also have the data for robotization.

There are 5,336 protest events in CLB and 22,414 in CASM in that time period. To summarize a measure for protest, we calculated the number of protests in an industry-province-year cell. There are 31 provinces in China. We defined 10 industries. The CLB dataset already coded each industry into mining, manufacturing, construction, services (which includes retail), transportation, education, and "others". We recoded protest events in CLB that have been assigned to "other" as agriculture (for descriptions like "agriculture", "farm", "forestry" and "park"), electric (for "power plant", "oil", "energy", "hydropower", "electric"). In addition, we recoded some service protests into medical ("medical", "hospital", "doctor", "nurse"), and some manufacturing protests into computer industry protests ("computer", "internet", "technology", "software", "information" and "electronic") to generate a more find-grained industry coding scheme. For cells that lack observations, we replaced it with zeros. The CASM dataset does not have industry coding. We used dictionary methods to code each protest in CASM into the

[7] Zhang and Pan (2019) have shown that censorship algorithms focus on large protests, but for the large protests with thousands of tweets discussing them, there are always remaining posts on social media that escaped censorship. On the other hand, censorship algorithms allow discussion of small protests with only a few tweets since they cannot trigger major mobilization. Hence, using pre-censored validation data, Zhang and Pan (2019) found that censorship contributes to less than 10% of underestimation of protests on Weibo. Still, they have not compared whether censorship's effect on under-coverage is changing over the years. CLB, on the other hand, has no formal documentation explaining whether censorship may impact their data collection process.

previous categories. We compiled a list of words associated with each industry. Each protest is coded to a category if its description contains more words in that category than words in other categories. Our keywords are provided in Appendix Table A1.

The dependent variable is the number of robots per 1,000 workers calculated at industry-province-year and province-year level, as we explicate below. The robot data come from the International Federation of Robotics (IFR). They define an industrial robot as an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes", following the definition of the International Organization for Standardization (ISO).[8] One limitation of the IFR data is that robotization only covers a small segment of automation, focusing on the manufacturing sector and routine service sector, and does not capture forms of automation such as artificial intelligence and software that could impact the non-routine service jobs. Data are available from 1993 to 2015. However, the high missingness and high share of industry-unallocated robots prior to 2010 and the fact that the explanatory variable is only available since 2011 restrict the data to the period from 2011 to 2015. To correspond to the protest industries, we selected agriculture, mining, manufacturing, electronics (which corresponds to the computer industry), medical devices,[9] automotive and other vehicles (corresponding to transportation), electricity, gas and water (Electric), construction, education/ research/ development, and other non-manufacturing (services). For the unspecified robots that make up between 20-45% of the total in the given year, we allocated them proportionately to each industry's total share of robots. Notably, the IFR robot data are only available at national and industry level, but we wish to explore local variations in protest counts. The lack of local

[8] https://ifr.org/industrial-robots

[9] Electronics and medical devices are nested in manufacturing, so we subtracted them from manufacturing. Medical devices, in turn, are nested into electronics, which also requires a subtraction.

variations in the IFR robot data is a common challenge faced by other quantitative research using IFR robot data (see Acemoglu and Restrepo, 2020). We used two different approaches to extrapolate the national-industry level IFR data at the local level.

Our first measure of industry-province-year level robot density variable is extrapolated from the IFR data and industry employment count from the National Bureau of Statistics of China (NBS, *guojia tongjiju*).[10] The extrapolation formula is

$$Robot\ Density_{i,p,y} = Employment_{ipy} * \frac{Robot_{iNy}}{Employment_{iNy}}\ ,\ (1)$$

where $Robot_{ipy}$ is the industry-province-year level robot density and $Robot_{iNy}$ is the industry-national-year level robot density. $Employment_{iNy}$ is the industry-level employment count for China. $Employment_{i,p,y}$ is the number of employment in industry i in province p at year y. Essentially, we explore the variation of provincial employment share in certain industries (e.g., Guangdong Province in China has more workers than other provinces) compared with national-average to obtain measures of industry-province-year level variations.[11] This measure assumes that the ratio between employment and robot, at the national level, is the same as the ratio between employment and robot, at each province level. We call this robot density measure IPY (industry, province, year).

The construction of the IPY measure relies on the rather strong assumption that national-level robot to employment ratio is the same in different provinces. Following Acemoglu and Restrepo (2020) Equation (11), we added a second robot density measure with a shift-share design. Shift-share design, also referred to as Bartik instruments, is a commonly used techniques

[10] http://www.stats.gov.cn/english/Statisticaldata/AnnualData/
[11] Our equation differs slightly from the original Equation 17 used by Acemoglu and Restrepo (2020) because they used robotization with time variation, while we calculate robot values for each year separately.

in economics to construct measures of regional-year-level variables from regional-industry-level variables and industry-year-level shocks (Bartik 1991; Goldsmith-Pinkham et al. 2020). In this article, we construct measures of province-year-level robot density from industry-year level robot density (from IFR dataset), and industry-province-level employment share as weights (the industry-province-level employment data come from the National Bureau of Statistics). The detailed formula for calculating robot density using shift-share design is given in the Appendix. The advantage of shift-share design is that it allows more regional-level variations in robot and employment ratios, while the disadvantage is that shift-share design is a province-year level variable, not province-industry-year level variable as the IPY measure, which leaves fewer cases to work with. The main results report the effects on IPY robot density and shift-share (PY) robot density. Most results are consistent regardless of the measures of robot density used.

There are various economic and demographic characteristics that could affect varying levels of protest and robotization. We draw these data from the National Bureau of Statistics. They exist in all years at the province level for the total population, percent female, percent college-educated, the old age dependency ratio (number of age 65+/ number of age 18-64) the unemployment rate, GDP per capita in yuan, and at the industry-province level for average wages in yuan. Industry-province employment is another possible control variable but has not been included in the analysis due to collinearity with the robot density variables. For some of the province-level demographic variables like population, sex and college, the 2015 values are much higher than for the other years, which might reflect a measurement error, so for that year we took the average between 2014 and 2016. The industry concordance used to merge data from the four data sources are in the appendix (Table A2), as well as the precise table numbers drawn from the NBS for the control variables (Table A3). The descriptive statistics is found in Table 1.

INSERT TABLE 1 HERE

There is some missingness in the wage variable (3.6%). The higher missingness in the two protest variables merely suggest that the remaining cells have no recorded protest incident, so in the main regression tables we report models in which missing observations in the protest variable have been filled with zero.

Method

Does the rising number of protests result in more automation? Or does more automation lead to job losses and salary reduction, which creates labor protests? Reverse causality is a major concern for our proposed relationship between protests and automation. Panel data have been often employed for determining causal order from observational data (Vaisey and Miles, 2017). Luckily, we have panel data for both of our protest events and our robotizing measures, which allow us to use statistical methods to mitigate the reverse causality concern. Nonetheless, we discuss the possibility of reverse causation in the limitations.

We mainly used Arellano-Bond estimator, which is a dynamic panel model that takes the first difference over time across variables to remove time-invariant unobserved confounders (Arellano and Bond, 1991). The Arellano-Bond estimator is popular in econometrics and has been recently introduced to the sociology literature (Allison et al. 2017). We use the following equation:

$$\Delta RobotDensity_{i,p,} = \beta_1 * \Delta RobotDensity_{i,p,(y-1)} + \beta_2 * \Delta Protest_{i,p,y} + \beta_c * Controls_{i,p,y} + \Delta\varepsilon_{i,p,y}. \quad (2)$$

Where industry (i), province (p) and year (y); Δ is the first difference over time (e.g., Δrobot density$_{i,y}$ = robot density$_{i,p,y}$ − robot density$_{i,p,y-1}$).

The Arellano-Bond estimator uses the lagged dependent variable as instrumental variable (IV) for the first-difference of the outcome. In other words, robot density$_{i,p,y-2}$, robot density$_{i,p,y-3}$ etc. are used as the instrumental variables of the first-differenced outcome, Δ robot density$_{i, p, y-1}$. The Arellano-Bond estimator can consistently estimate the causal effect with a sufficiently large dataset even when reverse causality is present. In practice, generalized method of moments (GMM) methods are used for estimation. We used the R package *plm* and its function *pgmm* to fit the Arellano-Bond estimator. The limitation of the Arellano-Bond estimator is that it may also have a downward bias in estimating effects when the sample size is small, which is not a concern in our case since we have over 1,500 observations in our main equation.

We also applied the cross-lagged panel model proposed in Allison et al. (2017), which improves some of the shortcomings of the Arellano-Bond estimator by using a Maximum Likelihood Estimation procedure, instead of the generalized method of moments (GMM) estimator used in the original Arellano-Bond estimator. Unfortunately, the cross-lagged panel model is relatively new in the literature, and we find that the implementation of the cross-lagged panel model (*dpm*) is not stable enough across all model specification, especially when control variables are included in the model. Therefore, we present the estimated results using Arellano-Bond estimator in the main text and present the cross-lagged panel model estimation results for robot density IPY in the appendix. (For robot shift-share at the province-year level, there are insufficient observations to execute the model.)

We run CLB and CASM protests in separate regression models because they have different methods for capturing and including protest events. In addition to the Arellano-Bond estimator and cross lagged fixed effect model, we explored robustness checks including various alternative definitions of protest used in CASM and CLB. We also estimated the effects on IPY robot density at the province-year level and repeat the main models using province fixed effects with lagged outcome variables. The results are similar to what we found from the Arellano-Bond estimator. [12]

Results

Table 2 reports the result of the Arellano-Bond estimator using the robotization measure at the industry-province-year (IPY) level. Note that for this Table and Table 3, we used robust standard errors formula proposed by Windmeijer (2005). For CLB protest (column 1-3), the baseline model shows that an increase of one protest is associated with 0.1 additional robots per 1,000 workers ($p<0.01$). This relationship still holds after accounting for province-level controls (0.0915, $p<0.01$) and the wage and employment controls (0.089, $p<0.01$). Considering that the mean of the dependent variable is 0.757 (Table 1), the effect of one more protest translates into around 11.7% to 13.2% increase in additional robot per 1,000 workers.

Columns 4-6 report the Arellano-Bond regressions for CASM protest, and we again find a statistically significant positive association with robotization although the size effect is smaller than for CLB protests. In the base and full models, we report that an increase of one protest reported in CASM is associated with an increase of 0.02 robots per 1,000 workers ($p<0.01$ and $p<0.05$), though the coefficient is somewhat smaller in the full model. The results translate into

[12] Leszczensky and Wolbring (2019) and Vaisey and Miles (2017) find that fixed effect models with lagged outcome variables are inferior to Arellano-Bond estimator and cross lagged fixed effect models.

2.64% increase in the number of robots per 1,000 workers. Still, considering that it is the effect of one more protest, the effect size is not small.

INSERT TABLE 2 HERE

Table 3 presents the Arellano-Bond estimator regression results for the shift-share measure of robotization, which are applicable at the province-year level. We still find positive coefficients for both CLB dataset (0.10, $p<0.01$) and the CASM dataset (0.01, $p<0.1$). Note that the effect size is similar to that in Table 2 for each dataset. We again find that the size effect is smaller for the CASM dataset than for CLB dataset. The difference in the scale of effect could be because the CASM dataset is machine-predicted, and the CLB dataset is human verified. Recent research has found that using machine-predicted variables in a regression may lead to attenuation bias (Zhang 2021).

INSERT TABLE 3 HERE

The models reported in this paper show that increasing labor contention that takes the form of protests is associated with more automation in the form of robotization. The labor sociology and political economy implications are further explored in the Discussion section.

Robustness Checks

All robustness check models are reported in the appendix. To assure the robustness of the protest variables, we used alternative variables reported in the protest datasets. We first provide a placebo test by testing the relationship between the share of non-labor protests (compared to the total) and robotization. In CASM, labor protests only constitute 24% of protests in China; the remaining protests are non-labor protests, including peasants' protests against land-grab from the government, city middle class's protests against real estate developers, environmental protests, protests against corrupt government officials, protests related to medical or education rights, among others. If political economy considerations for automation only apply in the labor context (regarding workers' political power and wages), we should assume an indeterminate or negative relationship between non-labor protests and robotization. Indeed, we find that this relationship is indeterminate for the robot IPY measure and the shift-share robot measure (Table A4).

CASM also label each protest's tactic as violent, disruptive, or peaceful.[13] We tested the relationship between the share of violent protests and robotization. More violent protests involving clashes with the police and local authorities could prove more traumatic to factory owners, who might be more inclined to automate under these circumstances. However, we do not find this empirical connection. In fact, the relationship between share of violent protest and robotization is indeterminate (Table A5). One possible explanation is that CASM does not distinguish violence initiated by protesters and by their targets, such as companies or the government, and thus there is misclassification error. In other words, if companies initiate violence, it might be a lesser cause for automation. Another possible explanation is that there are also high employer costs for non-violent protest dispute resolution that rely on labor arbitration

[13] In CASM's definition, disruptive protests are non-violent. They seek to disrupt social order, such as blocking streets or government offices, to attract attention from bystanders and to force the government to react (Cai 2010).

and state-mediated conflict resolution with favorable outcomes for workers (Lee 2007; Su and He 2010).

CLB reports protest activity in private-sector companies. Case studies in private-sector labor protests show that while the central state unions tend to limit strike action via concessions or mediation (Friedman 2014), rank-and-file union activists and workers do initiate strikes and protests (Chang and Cooke 2018), thus raising the question whether private sector employers behave differently with respect to automation than the public-sector or SOE. We do not find a statistical difference in robotization between private-sector company protests and other sectors (Table A6).

We also investigate the link between strike action and robotization. Strikes are a form of contentious labor activity in China that have generated a push to higher wages and bargaining power, especially since 2008 (Elfstrom and Kuruvilla 2014). CLB records over a hundred unique protest actions, ranging from strikes to sit-in, protest, threatening to jump off a building, cutting power or dumping trash. Often a strike is done in combination with other actions, so we coded any action that includes the string "strike" and calculate the share of protests involving a strike. We do not find that the presence of strike is associated with more robotization (Table A7). Strikes are not necessarily a more contentious form of protest that provoke more automation.

In another robustness check, we repeated the province-year regressions for the IPY robot density measure summarized as PY rather than the shift-share measure and we find a positive association in line with the main results (Table A8). Applying the province fixed effect model confirm the findings presented in the main results, except for CASM when accounting for the controls, though the coefficients remain positive (Table A9 and A10).

We applied the cross-lagged fixed effect model proposed in Allison et al. (2017), as discussed in the methods section. We also obtain positive coefficients for protests with very low standard errors (Table A11 and A12). By using the Arellano-Bond estimator in the main result and cross-lagged fixed effect model in robustness checks, we rule out the possibility that this positive association is solely due to reverse causation. Certainly, we do not claim that the reverse causal story does not exist. Instead, our statistical analysis confirms that reverse causation cannot explain the observed statistical association between protests and automation, after considering their time orders in the statistical analysis.

We examined whether automation occurs differently in high protest observations (above median) compared to low protest observations (below median). We find that for below median CLB protests robotization occurs at twice the rate and for below median CASM protests robotization occurs at four times the rate of high protest observations (Table A13). This could suggest that employers are especially inclined to automate at low levels of protest while in areas where protests are already common, and automation is already fairly widespread bringing even more automation is less likely. This still upholds the main results given the consistently positive relationship between protest and automation.

Our empirical evidence supports our theory that the number of protests predicts future robotization. We also performed a placebo test by showing that this effect should not occur when it is not expected to. Specifically, we tested whether the change of protests (2012 to 2015) is correlated with automation at an earlier period (2011) (it should not since the time order is reversed). We find that a barely significant positive relationship applies to CLB protests and robotization ($p < 0.01$), though the effect size is much smaller than for the main results, and for

CASM protests the relationship is negative and is not statistically significant (Table A14). Thus, we do not find consistent evidence that change in protests affect automation in an earlier period.

In a further robustness check, we ran an interaction between high robot industries (manufacturing, computer, and transportation) that account for the most available robotic stock and protests and find that it is primarily in these three industries that increased protests are associated with a higher robot density, while in low robot industries the frequency of protests has no relationship with robot density (Figures A1, A2).

To test whether the protest effects are driven by a subset of provinces, we repeated the regressions for each province and find that Guangdong, Hunan and Jiangxi are the key provinces for which this positive relationship holds, though there is no province for which we find a negative effect on robotization (Figure A3).

Overall, the robustness checks confirm the positive association between protests and robotization with the exception of the shift-share FE models for CASM protests.

Discussion

There are two important concurrent trends within Chinese industrial relations. Firstly, there is a rising contentiousness within workplaces, which have been linked to the poor representation of autonomous trade unions that advocate for labor interests as well as the continued high demand for Chinese manufacturing workers, who have fueled the Chinese development model since the late-1970s. Secondly, the advancement of robotics and artificial intelligence has made China the biggest market for robotics, even though its robot exposure is still less than more developed countries like South Korea or Germany. The drive toward robotics is explicitly encouraged by central and provincial government policy given the awareness of international competition for maintaining market share in global production chains. The need to remain competitive becomes even more acute with the shrinkage of the labor force given decades of fertility control policies and incentives for more affluent city-dwellers to reduce the number of children. The need to remain internationally competitive and labor shortage-linked wage rises are plausible explanations for increased automation in Chinese workplaces.

The central argument advanced in this paper is that in addition to these factors more widespread labor protests can partly account for the growth of automation. We have presented the first study to our knowledge that tried to empirically establish the link between labor upheaval and automation. Given the strong relationship between protests and robotization across most though not all models, we think that political economy plays an important role in the story of automation in China. Specifically, it means that protests are workers' means to fight for higher wages in the absence of functioning independent labor unions; they are a contestation for social power vis-à-vis the employer and the state; and, in extreme cases, can generate the negative publicity (e.g. Foxconn) that accelerates employers' incentives to automate production.

An important limitation of our analysis is that we do not offer a strictly causal claim about protests and robotization even with the statistical models applied in this paper. A potential reverse causal pathway is that the increased presence of robots could encourage more labor protests, because workers complain about de-skilling (Olzak 1989) or want wage rises and share in the company surplus. Furthermore, displaced workers (potentially via technology or general industrial restructuring) are known for aggregating in "rightful" street protests to pressure the state to give them more social benefits (Lee 2007). Guintella and Wang (2019), for instance, attribute strike activity (only using the CLB, not the CASM data) to robot exposure. In our account, the capitalist and state desire to weaken labor via automation is due to labor protests (see Foxconn case and Pun 2016). In the alternative account, layoffs due to automation create labor discontent (Lee 2007; Guintella and Wang 2019). While neither the other authors nor we are able to tease out the cause and effect definitively, both of our studies establish the positive relationship between protests and automation and the possibility that they are mutually reinforcing and compatible: strong labor protests due to poor working conditions or wage arrears make automation more attractive for firms, while later automation-induced layoffs trigger protest action, which justifies even more future automation.

Data limitations exist for both the protest data from CLB and CASM, as well as IFR. Both CLB and CASM data likely involve a substantial undercount of true protest events. It is hard to know what direction the bias takes as data quality might vary between years for CLB because the data collection procedure is not known. Future research could potentially address whether CASM data has a systematic undercount bias over the years. The CASM collection procedure has been documented in Zhang and Pan (2019). IFR robotic data does not exist at a fine-grained plant/ employer level, and the limited ISO-based definition of an industrial robot does not capture other forms of automation like computer software or AI algorithms. The latter is a major emphasis of Chinese tech companies and the party state.

We also need more empirical studies that capture the state's role in mediating and shaping automation. The Chinese state's push to automate coupled with their highly repressive labor regime, in which independent labor unions fail to take hold (Friedman 2014; Fu 2017) implies that the state mediates protest and automation by (1) reacting to labor unrest and offering minimal concessions and (2) accelerating automation to prevent future unrest. The state intermediation of automation works alongside the direct effect of protest on automation. Finally, we lack qualitative evidence that would confirm the political-economic and sociological motivation for Chinese employers to invest in automation. Going forward, more studies on the determinants and causes of automation are needed.

Implications

Labor protests are an important contributing factor to automation. Prior studies on labor unions show that there is a tradeoff between labor organization, wages and full employment, as more automatable occupations with high union coverage retain high wages but at the cost of sharp future declines in employment (Parolin 2021). Similarly, strike/ protest activity can temporarily wrest bargaining power and wage concessions from employers but at the cost of losing future employment as automation becomes a more attractive option for employers.

In the short run, rising level of automation and its associated inequality might increase the level of protest activities, if workers realize the danger and push government agencies to make policy concession to protect traditional industries. Indeed, we have seen similar protests organized by taxi drivers to force governments to ban gig economy services such as Uber and Lyft. The anti-automation stance is exemplified by British textile workers, called Luddites, smashing the machines in the early nineteenth century (Frey 2019). In the long run, if the speed of automation is fast enough such that the number of laborers or labor organizations from which mobilization can draw resources is shrinking, we may see a decreasing number of labor protests, or even the disappearance of traditional labor protests (e.g., strikes). To draw an analogy, there is a decline in union-led protests organized by industrial workers in developed countries after the WWII, due to the declining size of the manufacturing industry (Clawson and Clawson, 1999;

Kerrissey and Schofer 2013; Silver 2003). If the robotics revolution continues the same problem that is currently facing the western developed world could engulf China: technologically induced unemployment/ underemployment and even more drastic inequality (Sharif and Huang 2019; Rozelle and Hell 2020). This rising unemployment could cause structural grievances and create mobilization potential for other non-labor protests, and other political outcomes (e.g., the rise of far right in the US and Europe, see Frey et al. 2018; Annelli et al. 2019; Im et al. 2019). The interplay between labor unrest and automation is becoming even more salient as the global economic slowdown post-COVID intensifies, total debts rise, the working-age population shrinks, and firms face increasing pressure to automate production as quickly as possible. While our empirical results are confined to China, the relationship between labor protests and automation could hold in countries that have similar trajectories of labor-intensive industrialization, though generalization is difficult given the peculiar circumstances of a powerful, repressive state and state-intermediated labor relations in China. In settings where state controls of labor protest and state promotion of automation are absent, their relationship could be weaker, but this possibility raises the need for future research in labor protests and automation.

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Figure 1: Robot Density and Labor Protests in China, 2011-2015

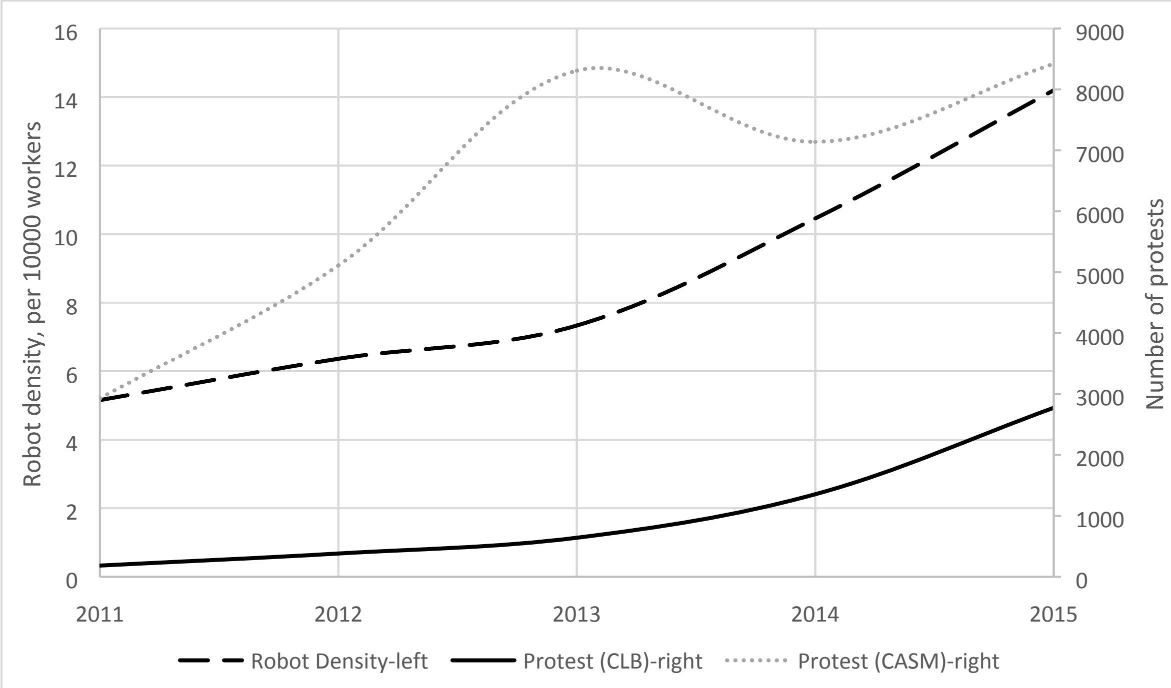


Table 1: Descriptive Statistics: Protests and Robots

Descriptive Statistics: Protest and Robots

Statistic	N	Mean	St. Dev.	Min	Max
Robot Density, robot per 1,000 workers	1,519	0.757	3.236	0.000	78.974
Number of Protests, CLB	883	24.140	120.869	1.000	2,774.000
Number of Protests, CASM	1,308	16.549	28.251	0.000	362.000
% College	1,519	12.026	6.529	2.391	41.825
GDP per capita, 1000RMB	1,519	55.361	26.029	6.189	129.381
Old Age Dep	1,519	12.531	2.677	6.710	20.040
Population in 10million	1,519	3.715	2.444	0.257	14.017
% Female	1,519	48.776	0.891	45.741	51.081
Unemployment rate	1,519	3.320	0.647	1.200	4.500
Wage in 1000RMB	1,465	30.766	11.292	3.140	292.178
Non-Labor Protests	1,308	32.271	57.979	0.000	596.000
Violent Protests	1,308	9.612	16.429	0.000	222.000
Private Protests	687	3.084	6.297	0.000	46.000
Strike Protests	883	8.958	38.307	0.000	593.000

Table 1: Arellano-Bond Estimator Models, Protests Effects on Automation using IPY Robot Density

	Dependent variable:					
	Robot Density IPY					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Protests, CLB	0.098***	0.089**	0.089**			
	(0.032)	(0.042)	(0.042)			
Number of Protests, CASM				0.029***	0.023**	0.023**
				(0.010)	(0.010)	(0.010)
%College		-0.258	-0.267		-0.194	-0.200
		(0.188)	(0.193)		(0.154)	(0.157)
GDP per capita, 1000RMB		0.059*	0.059*		0.057*	0.057*
		(0.033)	(0.033)		(0.033)	(0.033)
Old-Age Dep		-0.099	-0.106		-0.064	-0.066
		(0.301)	(0.310)		(0.271)	(0.279)
Population in 10mio		0.198	0.195		0.242	0.243
		(0.129)	(0.128)		(0.148)	(0.149)
%Female		0.212	0.187		0.169	0.154
		(0.564)	(0.581)		(0.528)	(0.546)
Unemp Rate		0.217	0.219		0.124	0.125
		(0.543)	(0.568)		(0.517)	(0.541)
Wage in 1000RMB			0.003			0.002
			(0.005)			(0.004)
Observations	1519	1519	1519	1519	1519	1519

Note: *p<0.1; **p<0.05; ***p<0.01

Note: The dependent variable is robot density IPY. The lagged robot density variable is used as instrumental variable. All models used robust standard errors.

Table 1: Arellano Bond Estimator Models, Protests Effects on Automation using Shift-Share Robot Density

	Dependent variable:					
	Robot Density, Shift-Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Protests, CLB	0.177***	0.113***	0.107***			
	(0.034)	(0.018)	(0.018)			
Number of Protests, CASM				0.045***	0.016**	0.012*
				(0.007)	(0.006)	(0.007)
%College		0.383*	0.349*		0.685**	0.622**
		(0.209)	(0.208)		(0.329)	(0.305)
GDP per capita, 1000RMB		0.179***	0.153**		0.215	0.184
		(0.068)	(0.065)		(0.132)	(0.128)
Old-Age Dep		0.942***	0.735**		1.657***	1.340***
		(0.360)	(0.339)		(0.462)	(0.453)
Population in 10mio		0.959***	0.775***		1.327***	1.074*
		(0.279)	(0.300)		(0.507)	(0.576)
%Female		0.545	0.419		-0.075	-0.271
		(0.438)	(0.420)		(0.570)	(0.572)
Unemp Rate		-1.668**	-1.520**		-2.072*	-2.018*
		(0.713)	(0.740)		(1.062)	(1.053)
Wage in 1000RMB			0.129			0.188
			(0.103)			(0.218)
Observations	155	155	155	155	155	155
Note:				*p<0.1; **p<0.05; ***p<0.01		

Note: The dependent variable is shift-share robot density. The lagged robot density variable is used as instrumental variable. All models used robust standard errors.

Appendix Tables:

Formula for shift-share measure of robot density

$$\text{robot density}_{p,y} = \frac{\text{employment}_{p,i}}{\sum_i \text{employment}_{p,i}} * \text{robot density}_{i,y}$$

Where *p* stands for province; *y* for year; and *i* for industry.

Table A1: CASM Word-Industry Keywords

Industry	Words
'Services'	"环卫 (janitor)",'理发 (barber)','餐厅 (restaurant)','旅馆(hotel)','饭店(restaurant)','酒店(hotel)','贸易(trade)','零售(merchandise) ','食品(food)','超市(supermarket)','足浴(foot massage)','会所(clubhouse)','网吧(netcafe)','酒楼(restaurant)','证券(stock)','保洁(cleaning industry)','娱乐(entertainment)','咖啡厅(coffee place)','健身(bodybuilding)','联通(Unicom)','酒吧(bar)','物业'(property management),'管理(management)','度假(vocation)','美食(delicious food)','金融(finance),'投资 (investment)','保险(insurance)','银行(bank)','火锅(hotpot)','记者(journalism)','快餐(fast food)','电视(television)','美容(beauty industry)','宾馆(hotel)','KTV','4S(car dealer)','商贸(commercial business)','驾校(driving school)','按摩(massage)','导游(tour guide)','旅游(tourism)','购物(shopping)','连锁(chain store)','购物(shopping)','百货(grocery)','便利店(convenience store)','家居(home furnishing)','服装(clothes)','水果(fruit)','商场('mall'), '菜市场(farmer's market)','蔬菜(vegetable)'
Construction	"建筑(building)", "建材(building material)", '建设(construction)', "装修(decoration)",'小区(residential unit)','工地(construction site)','装饰(decoration)','中建(China State Construction Engineering Corporation)','中铁(China Railway Construction Corporation)','建设(construction)','万达(Wanda Group)','地产(real estate)','包工头(contractor)','回迁(reallocate)','工程(construction)','开发(construction development)','建工(construction group)','工地(construction site)','混

	凝土(concrete)','棚户区(Shanty town）','改造 (reconstruction/renovation)','置业(purchase property)','土地(land)', '耕地(rural land)','房产(housing property)','售楼(selling property)'
Transportation	"的哥(male taxi driver)", "的姐(female taxi driver)", '的士(taxi)', "出租车(taxi)",'运输(transportation)','网约车(ridesharing car)',"客车(coach bus)","司机(driver)", "黑车(illegal taxi)",'港务(port affairs)','集装箱'(shipping container),'公交(public bus)','火车(train)','货车(truck)','滴滴(Didi)','私家车(private car)','配送(delivery)','物流（logistic company）', '快递（delivery service）', '美团（Meituan)','顺丰(SF Express)','快运(express delivery)','运输(delivery)','汽车(car)'
Manufacturing	'制造(Manufacturing)','材料(material)','库存(stock)','仓库(warehouse)',' 丝厂(silk factory)','玻璃(glasses)','工厂(factory)','工业(industry)','鞋厂(shoe factory)','食品厂(food industry)','木业(wood industry)','女工(female worker)','工人(worker)','产业园(industry park)'
Electric	'电子(electronics)','芯片(circuits)', '存储(storage)','液晶(liquid crystal)"','电子(electronic)','光电(photoelectric)','LED','通信(communication)'
Computer	'计算机(computer)','网络(computer network)','社交(social networking)','软件(software)','信息(information)','硬件(hardware)'
Education	'学校(school)','小学 elementary school','中学 middle school','大学 university/college','老师 teacher','教师 teacher','罢课(student strike)',' 幼儿园(kindergarten)','学院(college)','幼教 early childhood education',' 职院 professional school','教育局 Bureau of Education'
Mining	'矿(mines)','铜(bronze)','井(well)','煤(coal)','焦化 coal carbonization'
Medical	'医疗 (medical)', '医院 hospital ','医生 doctor ','护士 nurse ','医保 medical insurance','门诊 clinic'
Agriculture	'农业 agriculture','耕地 rural land ','农场 farm','林业 forestry '

Table A2: Industry Concordance

China Statistical Bureau	International Federation of Robotics	China Labor Bulletin (HK)/ Collective Action Social Media (CASM)

Agriculture, Forestry, Animal Husbandry and Fishery	Agriculture, forestry and fishery	Agriculture (recoded from Other)
Production and Supply of Electricity, Heat, Gas and Water	Electricity, gas, water supply	Electric (recoded from Other)
Information Transmission, Software and Information Technology	Electrical/Electronics (excl. Medical devices)	Computer (recoded from Other)
Health and Social Services	Medical, precision, optical instruments	Medical (recoded from Other)
Mining	Mining and quarrying	Mining
Manufacturing	Manufacturing (excl. Electronics and automotive/ transport)	Manufacturing
Construction	Construction	Construction
Transport, Storage and Post	Automotive, Transport	Transportation
Scientific Research and Technical Services; Education	Education/research/developm ent	Education
Wholesale and Retail Trades; Hotels and Catering Services; Financial Intermediation; Real Estate; Leasing and Business Services; Management of Water Conservancy; Environment and Public Facilities; Service to Households, Repair and Other Services; Culture, Sports and Entertainment; Public Management, Social Security and Social Organization	All other non-manufacturing branches/ Services	Services (merged with Retail)

Table A3: Control Variable Table Numbers As They Appear in National Bureau of Statistics of China[1]

	2011[2]	2012	2013	2014	2015
TotalpopP[3]	3-10	3-5	2-11	2-11	2-11
OldAgeDepP	3-9	3-13	2-11	2-11	2-12
SexFemaleP	3-9	3-12	2-10	2-10	2-11
CollegeEducP	3-13/3-10	3-15/3-5	2-13/2-11	2-13	2-14
GDPcapitaP	2-14/3-10	2-14/3-5	3-14	3-15	3-9
UnemploymentRateP	4-17	4-17	4-17	4-17	4-17
WageIP[4]	4-16	4-16	4-16	4-16	4-16
EmploymentIP	4-5	4-5	4-5	4-5	4-5

[1] Drawn from National Bureau of Statistics of China (guojia tongjiju) Tables http://www.stats.gov.cn/english/Statisticaldata/AnnualData/

[2] The values from a given year are obtained from the NBSC Yearbook of the following year, i.e. 2011 data comes from the 2012 yearbook

[3] P is province

[4] IP is industry, province

Table A4: Robustness: Non-Labor Protest Ratio (CASM) and Automation, using Arellano-Bond estimator.

	Dependent variable:	
	Robot Density IPY	Robot Density, Shift-Share
	(1)	(2)
Non-Labor Protest Ratio, CASM	-0.017	0.071
	(0.023)	(0.429)
College	-0.210	0.624**
	(0.188)	(0.305)
GDP per capita, 1000RMB	0.074*	0.213
	(0.040)	(0.136)
Old-Age Dep	-0.062	1.401***
	(0.317)	(0.492)
Population in 10mio	0.304*	1.133*
	(0.176)	(0.638)
%Female	0.168	-0.516
	(0.629)	(0.646)
Unemp Rate	-0.012	-2.636***
	(0.606)	(1.014)
Wage in 1000RMB	0.003	0.260
	(0.005)	(0.226)
Observations	310	31
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A5: Robustness: Violent Protest Ratio (CASM) and Automation, using Arellano-Bond estimator.

	Dependent variable:	
	Robot Density IPY	Robot Density, Shift-Share
	(1)	(2)
Violent Protest Ratio, CASM	0.125	0.214
	(0.099)	(1.111)
College	-0.251	0.622^{**}
	(0.203)	(0.302)
GDP per capita, 1000RMB	0.075^{*}	0.211
	(0.042)	(0.137)
Old-Age Dep	-0.112	1.415^{***}
	(0.363)	(0.485)
Population in 10mio	0.281	1.140^{*}
	(0.196)	(0.634)
%Female	0.181	-0.552
	(0.683)	(0.647)
Unemp Rate	0.176	-2.613^{**}
	(0.673)	(1.056)
Wage in 1000RMB	0.035	0.261
	(0.033)	(0.230)
Observations	310	31

Note: *p<0.1; **p<0.05; ***p<0.01

Table A6: Robustness: Private Company Protest Ratio (CLB) and Automation, using Arellano-Bond estimator.

	Dependent variable:	
	Robot Density IPY	Robot Density, Shift-Share
	(1)	(2)
Private Company Protest Ratio, CLB	-0.387	2.574
	(0.571)	(1.715)
College	-0.203	0.664**
	(0.198)	(0.299)
GDP per capita, 1000RMB	0.031	0.214
	(0.019)	(0.134)
Old-Age Dep	0.224	1.205***
	(0.487)	(0.463)
Population in 10mio	0.203*	1.062*
	(0.111)	(0.618)
%Female	-1.211	-0.429
	(1.262)	(0.620)
Unemp Rate	-1.226	-3.120***
	(1.001)	(1.021)
Wage in 1000RMB	0.045	0.285
	(0.084)	(0.221)
Observations	310	31
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A7: Robustness: Strike Protest Ratio (CLB) and Automation, using Arellano-Bond estimator.

	Dependent variable:	
	Robot Density IPY	Robot Density, Shift-Share
	(1)	(2)
Strike Protest Ratio, CLB	0.408	-1.583
	(1.205)	(1.091)
College	-0.198	0.638^{**}
	(0.189)	(0.276)
GDP per capita, 1000RMB	0.029	0.217
	(0.019)	(0.136)
Old-Age Dep	0.246	1.164^{***}
	(0.499)	(0.443)
Population in 10mio	0.185^{*}	1.095^{*}
	(0.111)	(0.629)
%Female	-1.230	-0.372
	(1.246)	(0.680)
Unemp Rate	-1.286	-3.082^{***}
	(1.050)	(1.126)
Wage in 1000RMB	0.047	0.288
	(0.082)	(0.229)
Observations	310	31
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A8: Robustness: FE Models for Protests and Automation using PY Robot Density, Province-Year. Standard errors are clustered at the province level.

	Dependent variable:	
	Robot Density IPY	
	(1)	(2)
Number of Protests, CLB	0.007*	
	(0.004)	
Number of Protests, CASM		0.013***
		(0.002)
College	-0.276*	-0.266**
	(0.155)	(0.124)
GDP per capita, 1000RMB	0.042	0.020
	(0.035)	(0.025)
Old-Age Dep	-0.305	-0.247
	(0.268)	(0.165)
Population in 10mio	0.090	0.090
	(0.148)	(0.124)
%Female	0.040	0.152
	(0.437)	(0.307)
Unemp Rate	0.196	0.750*
	(0.535)	(0.437)
Wage in 1000RMB	0.116***	0.035**
	(0.039)	(0.017)
Observations	31	31
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A9: FE Models, Protests Effects on Automation using IPY Robot Density, Lead DV with Lag DV in RHS. Standard errors are clustered at the province level.

Dependent Variable:	Robot Density IPY, 1Y Lead					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Number of Protests, CLB	0.0949***	0.0874***	0.0869***			
	(0.0061)	(0.0052)	(0.0052)			
Number of Protests, CASM				0.0175***	0.0135**	0.0133**
				(0.0044)	(0.0052)	(0.0055)
Robot Density IPY	0.1720***	0.1649***	0.1439***	0.2037***	0.1930***	0.1716***
	(0.0150)	(0.0149)	(0.0285)	(0.0127)	(0.0114)	(0.0279)
%College		0.1552	0.1507		0.1429	0.1369
		(0.1482)	(0.1439)		(0.1499)	(0.1461)
GDP per capita, 1000RMB		0.0107	0.0007		0.0141*	0.0042
		(0.0088)	(0.0165)		(0.0069)	(0.0151)
Old-Age Dep		-0.0943	-0.2028		-0.0400	-0.1473
		(0.1259)	(0.1561)		(0.1074)	(0.1377)
Population in 10mio		-6.366***	-5.619**		-6.15***	-5.381**
		(2.073)	(2.204)		(1.989)	(2.095)
%Female		-0.0866	-0.1249		-0.0956	-0.1320
		(0.1810)	(0.1963)		(0.1699)	(0.1857)
Unemp Rate		0.2352	0.4354		0.2001	0.3839
		(0.3386)	(0.3039)		(0.3408)	(0.3167)
Wage in 1000RMB			0.0461			0.0465
			(0.0425)			(0.0429)
Fixed-effects						
province	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,178	1,178	1,136	1,178	1,178	1,136
R^2	0.12193	0.13396	0.14584	0.10254	0.11478	0.12676
Within R^2	0.07643	0.08908	0.10279	0.05604	0.06891	0.08274

province standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A10: FE Models, Protests Effects on Automation using Shift-Share Robot Density. Standard errors are clustered at the province level.

Dependent Variable:	Robot Density, Shift-Share					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Number of Protests, CLB	0.0984***	0.0702***	0.0669***			
	(0.0076)	(0.0064)	(0.0067)			
Number of Protests, CASM				0.0363***	0.0111	0.0081
				(0.0079)	(0.0078)	(0.0077)
%College		0.3615**	0.3083**		0.4334*	0.3195*
		(0.1588)	(0.1407)		(0.2240)	(0.1841)
GDP per capita, 1000RMB		0.1265**	0.0951		0.2196**	0.1535*
		(0.0591)	(0.0568)		(0.0985)	(0.0849)
Old-Age Dep		0.6051**	0.4259		1.321***	0.8960**
		(0.2802)	(0.2544)		(0.4382)	(0.4037)
Population in 10mio		0.5929**	0.3868		1.119***	0.6740
		(0.2305)	(0.2536)		(0.3872)	(0.4058)
%Female		-0.3145	-0.3683		-0.3162	-0.3924
		(0.3521)	(0.3389)		(0.5346)	(0.4932)
Unemp Rate		-0.6121	-0.4212		-1.135	-0.8311
		(0.7610)	(0.7679)		(1.16)	(1.392)
Wage in 1000RMB			0.1238*			0.2531
			(0.0685)			(0.1503)
Fixed-effects						
province	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	155	155	150	155	155	150
R^2	0.91011	0.95149	0.95258	0.70982	0.86433	0.87229
Within R^2	0.7741	0.87809	0.88612	0.27079	0.65907	0.69332

province standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A11: Cross-Lagged Panel Models, Protests Effects on Automation using IPY Robot Density

MODEL INFO:
Dependent variable: IPY Robot Density
Total observations: 310
Complete observations: 269
Time periods: 2012 - 2015

MODEL FIT:
$\chi^2(39) = 5067.303$
RMSEA = 0.692, 90% CI [0.676, 0.708]
p(RMSEA < .05) = 0
SRMR = 7.862

	Est.	S.E.	z val.	p
CLB Number of Protest (t - 1)	0.050	0.003	17.715	0.000
% College	0.054	0.041	1.305	0.192
GDP per capita in 1,000RMB	-0.017	0.010	-1.574	0.115
Old-Age Dependency Ratio	-0.047	0.051	-0.912	0.362
Population in 10mio	0.165	0.062	2.646	0.008
% Female	-0.058	0.110	-0.528	0.598
Unemployment Rate	-0.076	0.191	-0.396	0.692
Wage in 1,000RMB	0.162	0.024	6.674	0.000
IPY Robot Density (t - 1)	0.163	0.059	2.755	0.006

Model converged after 2845 iterations

Table A12: Cross-Lagged Panel Models, Protests Effects on Automation using IPY Robot Density

MODEL INFO:
Dependent variable: IPY Robot Density
Total observations: 310
Complete observations: 269
Time periods: 2012 - 2015

MODEL FIT:
$\chi^2(36) = 960.553$
RMSEA = 0.309, 90% CI [0.292, 0.326]
p(RMSEA < .05) = 0
SRMR = 0.243

	Est.	S.E.	z val.	p
CASM Number of Protests (t-1)	0.032	0.001	29.388	0.000
% College	0.020	0.014	1.443	0.149
GDP per capita 1,000RMB	-0.002	0.004	-0.613	0.540
Old-Age Dependency Ratio	0.001	0.017	0.076	0.940
Population in 10mio	0.004	0.020	0.189	0.850
% Female	0.043	0.038	1.144	0.253
Unemployment rate	0.017	0.065	0.262	0.793
Wage in 1,000RMB	0.010	0.008	1.250	0.211
IPY Robot Density (t - 1)	0.085	0.004	22.002	0.000

Model converged after 5378 iterations

Table A13: Above and Below Median Protest Effects on Automation using IPY Robot Density

	Dependent variable:			
	Robot Density IPY			
	High P	Low P	High P	Low P
	(1)	(2)	(3)	(4)
Number of Protests, CLB	0.038**	0.079***		
	(0.016)	(0.012)		
Number of Protests, CASM			0.010**	0.039***
			(0.004)	(0.005)
College	0.101	0.014	-0.058	-0.019
	(0.076)	(0.020)	(0.040)	(0.025)
GDP per capita, 1000RMB	0.015	0.007	0.009	0.0001
	(0.016)	(0.005)	(0.010)	(0.006)
Old-Age Dep	-0.215	-0.012	-0.030	0.008
	(0.142)	(0.033)	(0.078)	(0.035)
Population in 10mio	0.263**	0.054	0.126*	-0.021
	(0.133)	(0.035)	(0.076)	(0.042)
%Female	0.157	0.012	-0.057	-0.095
	(0.411)	(0.072)	(0.218)	(0.085)
Unemp Rate	-0.767	-0.004	-0.174	0.153
	(0.512)	(0.137)	(0.281)	(0.156)
Wage in 1000RMB	0.054***	-0.0001	0.113***	0.078***

	(0.018)	(0.012)	(0.022)	(0.013)
Constant	-6.310	-0.669	0.334	2.393
	(18.963)	(3.420)	(9.964)	(4.049)
Observations	402	238	456	426
R^2	0.117	0.253	0.123	0.272
Adjusted R^2	0.099	0.227	0.107	0.258
Residual Std. Error	5.395 (df = 393)	0.994 (df = 229)	3.173 (df = 447)	1.603 (df = 417)
F Statistic	6.503*** (df = 8; 393)	9.711*** (df = 8; 229)	7.838*** (df = 8; 447)	19.494*** (df = 8; 417)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A14: 2012-5 Change in Protests Effects on Automation in 2011. Fixed effect OLS regression at the province level Standard error has been used. Standard errors are clustered at the province level. Other independent variables have collinearity issues and we did not include their coefficients in the table.

	Dependent variable:	
	Robot Density IPY, 2011	
	CLB	CASM
	(1)	(2)
Number of Protests, CLB, 2012-5	0.005*	
	(0.0025)	
Number of Protests, CASM, 2012-5		-0.006
		(0.004)
Unemp Rate	-0.023	-0.067

	(0.055)	(0.059)
Wage in 1000RMB	0.006	0.007*
	(0.004)	(0.004)
Constant	0.771	-1.665
	(2.340)	(2.556)
Observations	299	299
R^2	0.184	0.089
Adjusted R^2	0.162	0.064
Residual Std. Error (df = 290)	0.516	0.546
F Statistic (df = 8; 290)	8.192***	3.538***
Note:		*p<0.1; **p<0.05; ***p<0.01

~~Table A14: 2012-5 Change in Protests Effects on Automation in 2011. Standard errorsOther independent variables have collinearity issues and we did not include their coefficients a~~

Figure A1: Predicted Values of Robot Density, CLB Protests

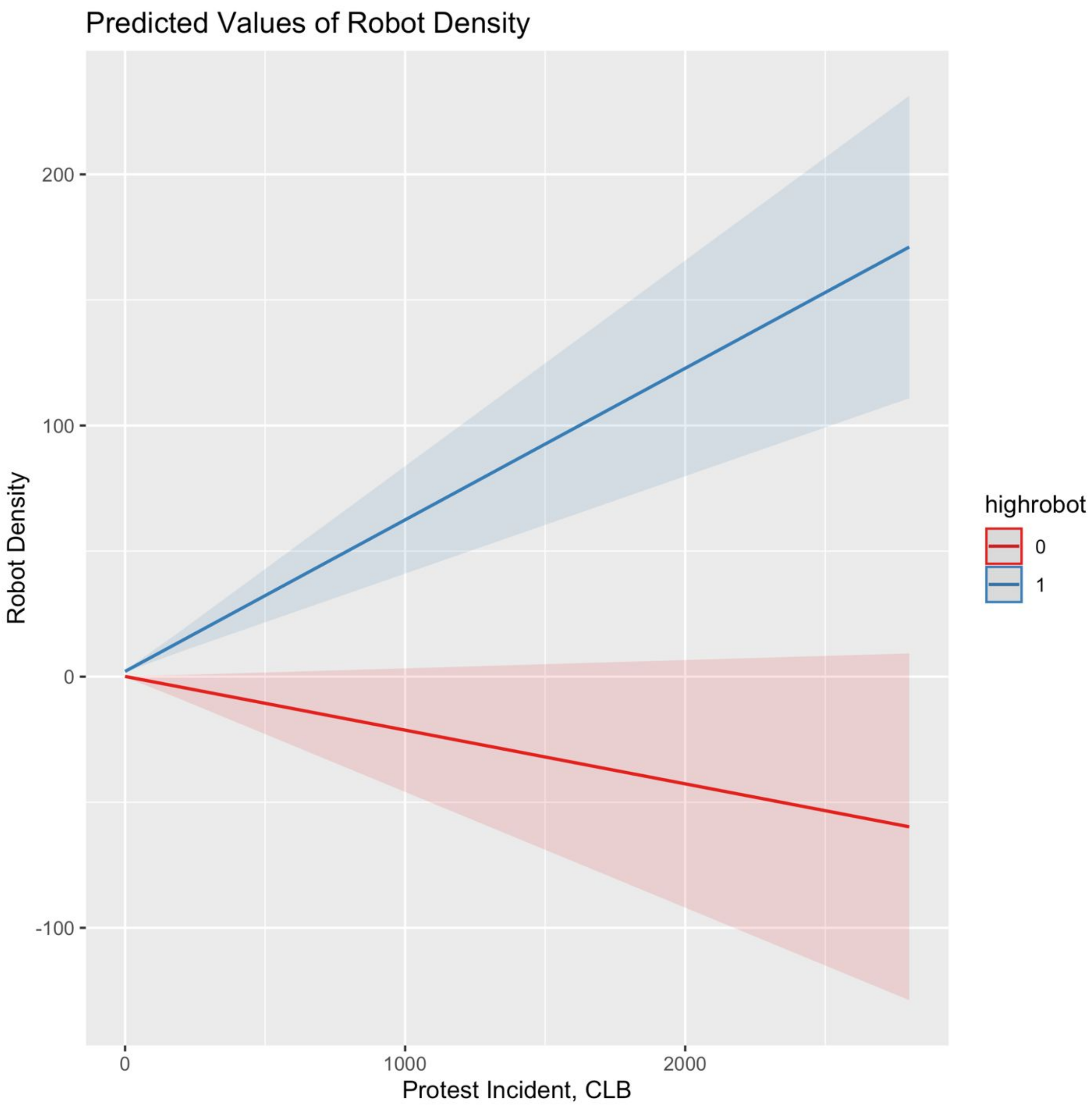
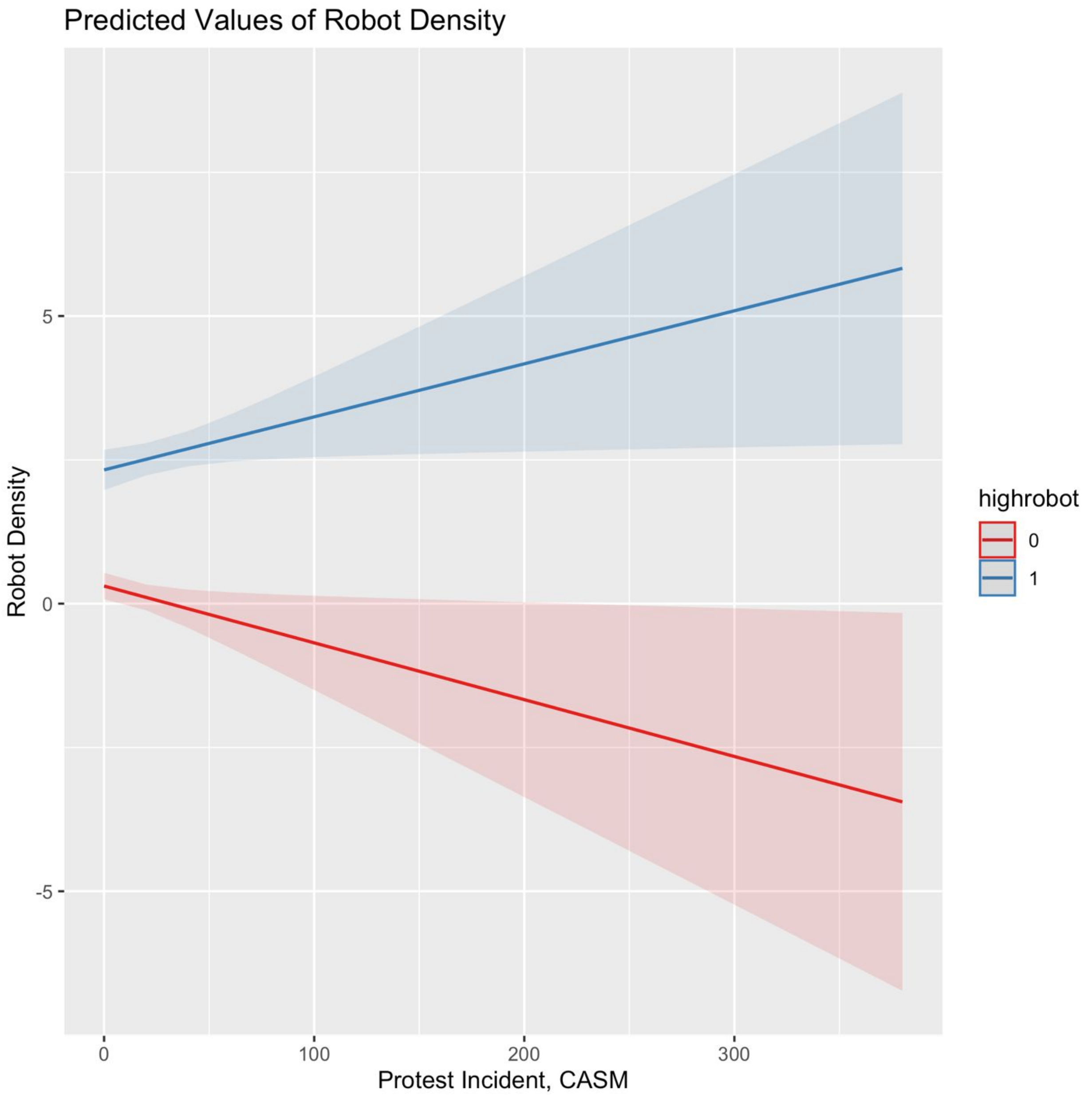


Figure A2: Predicted Values of Robot Density, CASM Protest



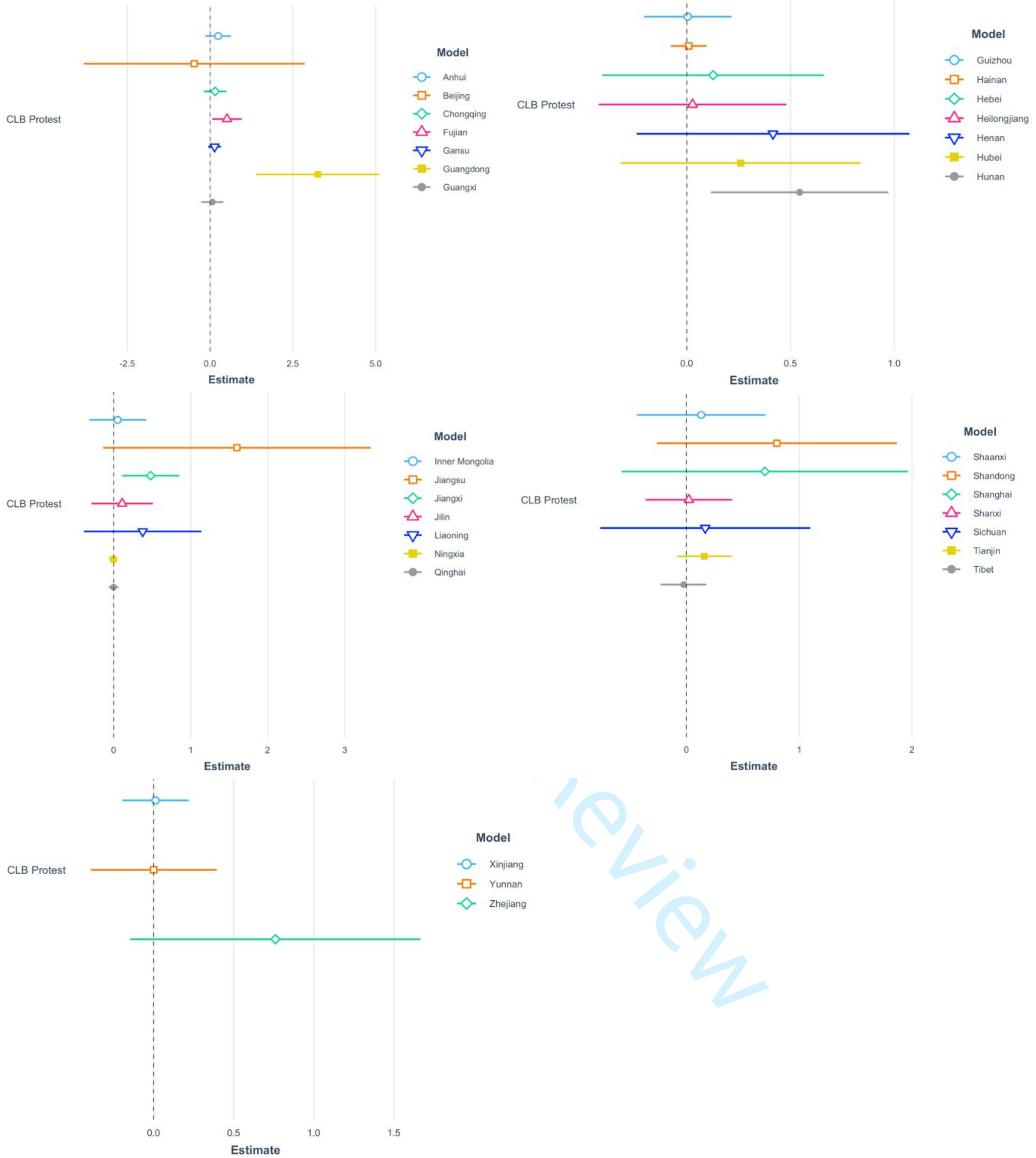


Figure A3: CLB Protest Effect on Robot Density by Province